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RESEARCH ARTICLE | FEBRUARY 21 2023

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AIP Conference Proceedings 2482, 020003 (2023)
https://doi.org/10.1063/5.0111803

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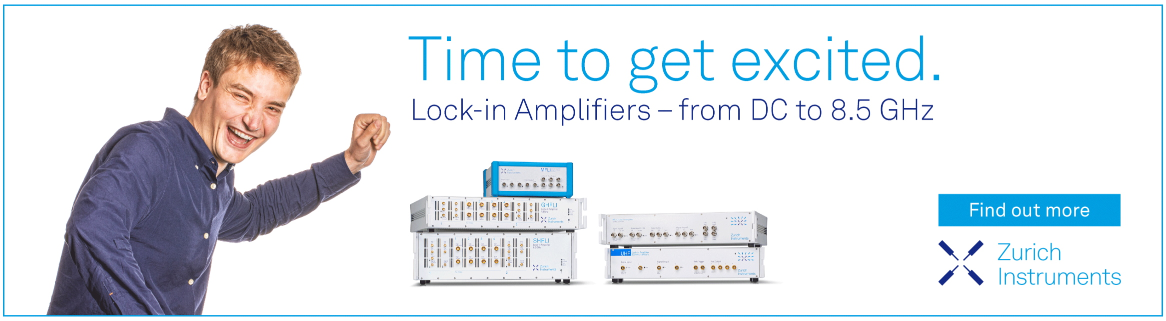

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Real Time Monitoring and Identification of Electrical Load Based on Artificial Neural Network

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Abstract. This research proposes a real time monitoring and identification of electrical load currents with non-intrusive load monitoring concept and Artificial Neural Network (ANN) based on feed-forward backpropagation training algorithm method. 5 types of single loads (lamp, TV, fan, refrigerator and dispensers) and 16 combined loads were simulated in this study. Sampling data from each load in the form of electric current quantities, will later be used as training data for ANN. Single electrical loads and their combinations are written in the form of numbers from 1 to 21. This number is used as target identification by the ANN algorithm. In order for ANN to recognize load patterns based on variations in input current, it is necessary to carry out a training process on the algorithm. This procedure will take some time, because it requires several repetitions of training to get a small error. The results of the overall ANN algorithm training will then be stored and will be used as the basis for the electrical load recognition process. The amount of electric load current that enters the ANN will be studied by the algorithm to be matched with the output form in the form of load combination groups. So that every change in the incoming electric current will be studied by the ANN algorithm and then matched with the output target in the form of the name of the load group. The training results show 2.729% small training error. The largest of output difference was occurred on 19th test with 19 state inputs and 18.51 neural network outputs. The smallest of output difference was occurred on 9th test, with 9 state inputs and 9.012 neural network output. The results show that the developed ANN algorithm identified electrical load usage accurately.

INTRODUCTION

Electricity bill sheet presents information about electricity usage by consumers every month. The issue that may arise is whether the use of electricity by consumers is in accordance with the information provided for electricity bills. The manual method used by power utility in calculating the amount of electrical energy used can be the cause of this problem. Error in determining the use of electrical energy is one result of the manual method used [1].

Electric current measuring devices record the use of electrical energy every hour, then multiplied by the basic electricity tariff of the electricity provider. The amount of electricity used by various electronic equipment that should be paid in one month by consumers is one important thing to know besides the total amount of usage.

Monitoring and recognizing electronic equipment that uses electrical energy is something that is tried to do in this research. In this way, consumers can know which equipment is operating and at the same time find out how much

The 3rd International Conference on Engineering, Technology and Innovative Researches
AIP Conf. Proc. 2482, 020003-1–020003-6; https://doi.org/10.1063/5.0111803
Published by AIP Publishing. 978-0-7354-4298-6/$30.00

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electricity consumption is consumed by each of these equipments. The proposed approach is a non-intrusive load monitoring (NILM) based monitoring system combined with an Artificial Neural Network (ANN)-based intelligent algorithm with the feed-forward backpropagation (FFBNN) training method. ANN is an artificial intelligence (AI) method like genetic algorithm (GA) and particle swarm optimization (PSO). Generally, the AI method is used to solve a complex problem [2, 3]. NILM is a measurement method that only requires a voltage and current sensor [4]. For pattern recognition and data classification, an artificial neural network-based information processing technique is used [5]. The use of electrical energy can be monitored and identified using the capabilities possessed by backpropagation neural networks in the process of pattern recognition and identification.

Previous studies can be found in the references related to electricity load. In [1] monitoring and identification in the household sector found a number of things that could be developed, such as a combination of small loads, so if another load combination appears then the neural network cannot recognize the load pattern, other than that the neural network algorithm used for identification is not optimal because it uses complex modeling with two software. References [6-8] investigate the NILM based load monitoring scheme. In [9] the electrical load identification technique has been presented with a more comprehensive approach to the NILM system, both in terms of the method and the technique used. In [10] discusses the use of NILM in monitoring loads for energy conservation. In some previous studies, monitoring load usage is only limited to displaying information on the amount of electricity is used, but does not provide information about which loads are operating. Then research on monitoring electrical loads is growing with the existence of intelligent methods [11, 12]. This method is used as a method for identifying load usage based on some given inputs. In [13] discusses offline monitoring of NILM-based and Neural Network loads. In [14] [15] discusses how to make a smart meter to monitor the use of electrical energy in the household sector by utilizing the concept of artificial intelligence. In [16] discusses the monitoring of load usage in industrial cases. In this present study, new form of modelling is used and load monitoring system is conducted in real time

RESEARCH METHOD

The proposed research method or procedure in this study is given as follows:

- The first step is signal conditioning from analog signals to digital signals.
- The second step is the measurement of the current value under steady state conditions of electronic equipment.
- The third step is the training and testing process to identify the condition of electronic equipment using neural network methods.

The hardware design consists of one current sensor, a signal conditioning circuit (rectifier), an arduino uno interface device, a laptop and five electronic devices as a load consisting of a TV, a lamp, a refrigerator, a fan and a dispenser. Prototype of the testing tool is shown in Figure 1.

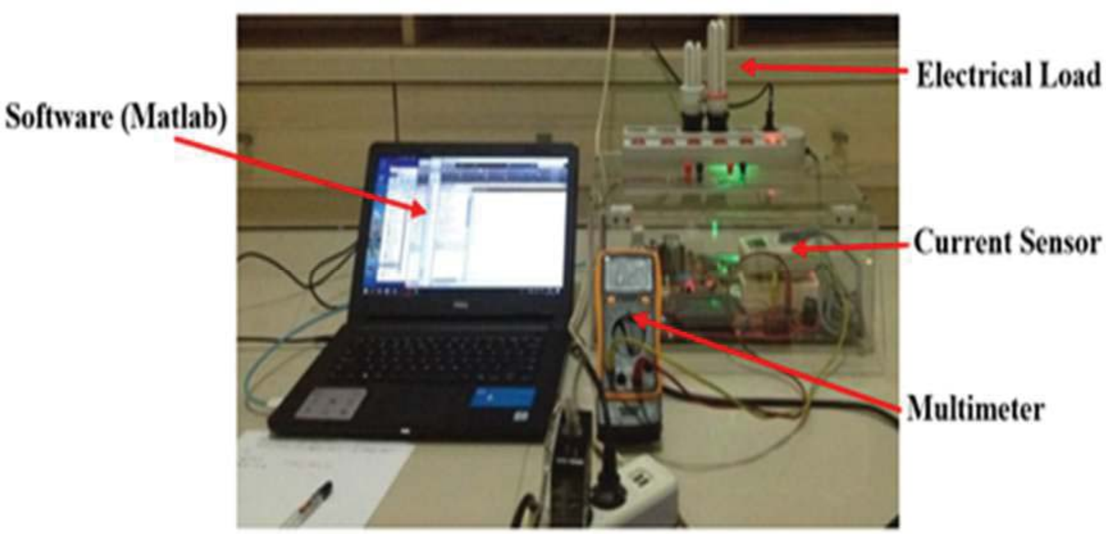

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FIGURE 1. Prototype testing

Figure 2 illustrates the test scheme used to monitor current waves from electronic equipment. This device consists of a step-up and step-down transformer, a 5volt power supply, an ACS712 current sensor, a microcontroller device (Arduino Uno), a signal conditioning circuit, a laptop and five electronic equipment as loads consisting of lighting lamps, TVs, dispensers, fans and refrigerator.

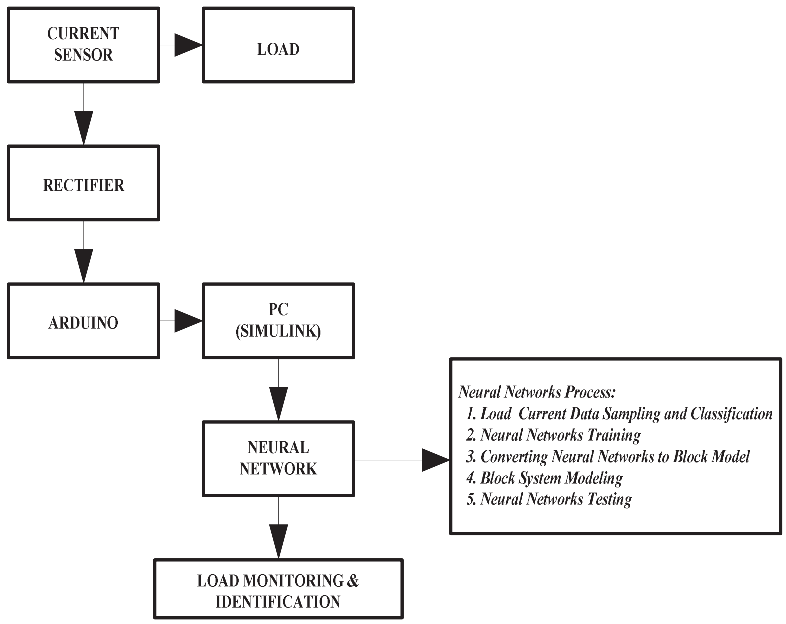

FIGURE 2. Testing Scheme

Load State

Total load is 5 single loads and 16 combination loads. Taking the sampling data flow of each load will be input data for network training. The amount of load data needed is 20 samples or 20 seconds. Each load combination is written in state, which is then used as an identification method by the neural network algorithm. The following table shows the load classification and current characteristics of each load combination.

TABLE 1. Load classification

State	Load	State	Load	State	Load
1	Lamp	8	TV+Lamp+Fan	15	Disp+Lamp+Fan
2	TV	9	Refrig+Lamp+Fan	16	Refrig+Disp+TV
3	Lamp+TV	10	Refrig+Lamp+TV	17	Disp+Lamp+Fan+TV
4	Fan	11	Disp	18	Refrig+Disp+Fan
5	Lamp+Fan	12	Disp+Lamp	19	Refrig+Lamp+Fan+Disp
6	TV+Fan	13	Refrig+Disp	20	Refrig+Fan+TV+Disp
7	Refrig	14	Refrig+Disp+Lamp	21	Refrig+Lamp+Fan+Disp+TV

ANN Modelling

After getting the current data from each load, the next process is to train networks. This procedure requires a rather long process, because to get a small error value, it requires several repeated training processes. From the experimental

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results, iterations / repetitions were carried out 7 times iteration. Based on the results of the training, obtained a small error of 2.729%.

Load Indicator Modeling

Study used 5 types of loads, with 16 load combinations. To make it easier for users to see the results of monitoring and identification, in addition to measuring features that can be directly read, then the load indicator is being made. For modeling the load indicator using the block lamp feature on Simulink. The following table shows a modeling example for a lamp load indicator, with the number of states consisting of 0, 1, 3, 5, 8, 9, 10, 12, 14, 15, 17, 19, and 21. All results can be seen in the Table 2.

TABLE 2. Load classification

Load	State
Lamp	0, 1, 3, 5, 8, 9, 10, 12, 14, 15, 17, 19, 21
TV	0, 2, 3, 6, 8, 10, 16, 17, 20, 21
Fan	0, 4, 5, 6, 8, 9, 10, 15, 17, 18, 19, 20, 21
Refrigerator	0, 7, 9, 10, 13, 14, 16, 18, 19, 20, 21
Dispenser	0, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21

System Modeling

The neural network is then converted into a block diagram, so that the response of the system can be seen in recognizing the pattern of the load or identification of the load as shown in Figure 3

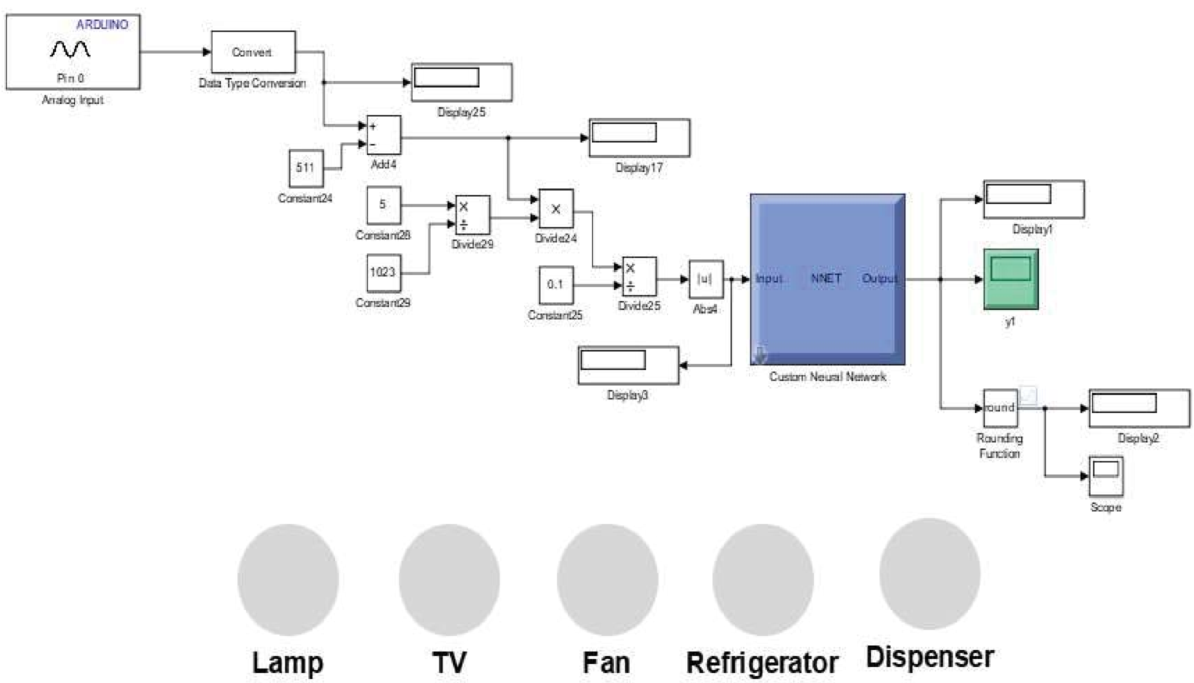

FIGURE 3. System modeling

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RESULTS AND DISCUSSION

Next, a load combination test is performed. There are 21 states / load combinations tested. Figures 4 and 5 show the results of monitoring and identification of load usage. For monitoring data (Figure 4), the input data is obtained from the current sampling data for each load, then the testing data is the result of monitoring at Simulink. In the identification data from Figure 5, the target data is a load / state combination data as in Table 1, then the testing data is the result of testing or identification of neural networks loads. From testing results, it is obtained the characteristics of monitoring and identification of the load current. The biggest difference is in the 19th test or state 19, where the neural network produces an output of 18.51. Meanwhile, testing with the smallest difference is in the 9th test or state 9 where the neural network produces an output of 9.012. Optimal results are obtained, where monitoring and identification process is accurate as indicated by a very small error. Here, it is applied a new model for monitoring and identifying the load current with the concept of NILM with the ACS712 current sensor combined with an intelligent method based on ANN with training methods based on feed-forward backpropagation.

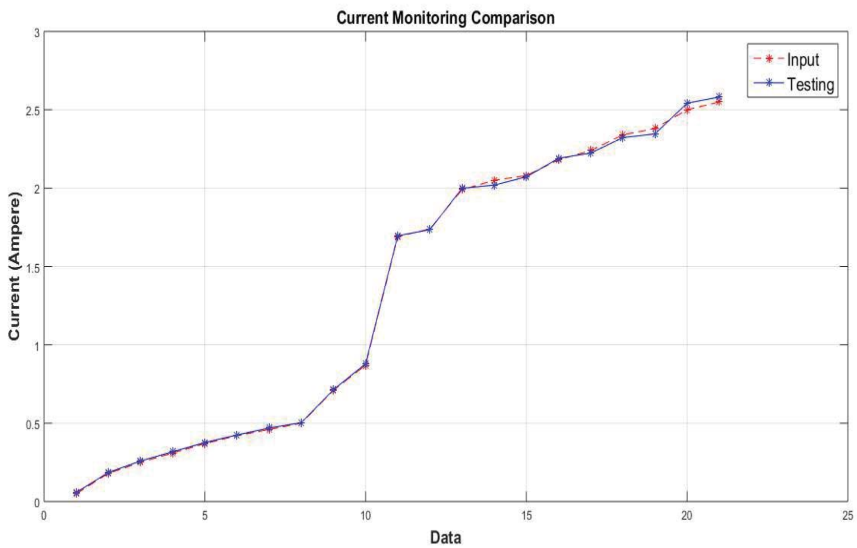

FIGURE 4. Comparison of load current monitoring

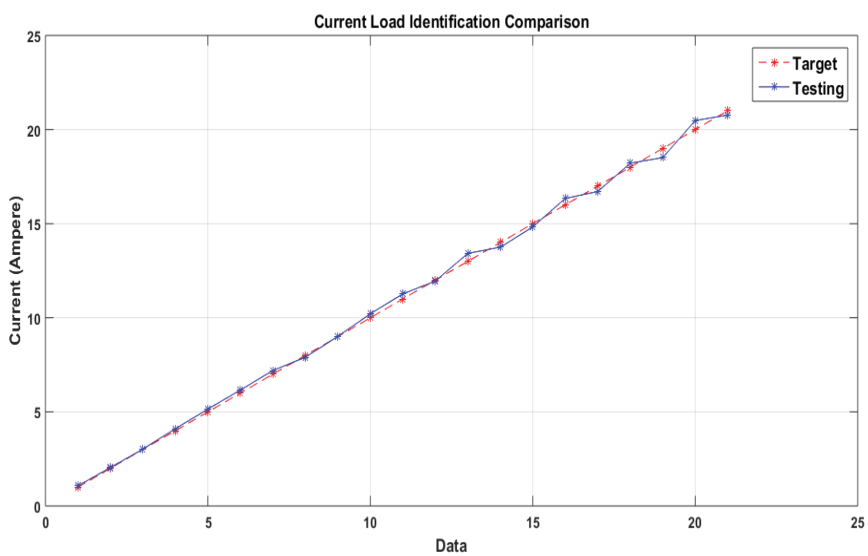

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FIGURE 5. Comparison of load current identification

CONCLUSION

This research proposes a model for monitoring and identifying load usage at home with the NILM concept using a neural network algorithm with a Feed-Forward Backpropagation training algorithm. Five different loads, namely lamp, TV, fan, refrigerator, and dispenser with 21 combinations were used as test scenarios. Of the 21 test scenarios, the most optimal results are obtained in the 9th test scenario where the neural network produces an output of 9,012. This shows that the 9th load combination is very close to the load recognition process carried out by the neural network, because the difference is only 0.012 adrift. Electrical load that can be monitored and recognized in each test scenario is a sign that the proposed system is declared to be able to work effectively.

REFERENCES

1. K. Hutoro, "Design of smart meters to monitor and identify the use of electrical energy in the household sector using backpropagation neural networks," thesis, Institut Teknologi Sepuluh Nopember, 2015.
2. Y. Yusran, Y.A. Rahman, I.C. Gunadin, S.M Said and S. Syafaruddin, 2020 "Mesh grid power quality enhancement with synchronous distributed generation: optimal allocation planning using breeder genetic algorithm", (Przegląd Elektrotechniczny, 2020), pp. 82-86.
3. Y.A. Rahman, S. Manjang, Yusran and A.A. Ilham, "Evaluating the effect placement capacitor and distributed photovoltaic generation for power system losses minimization in radial distribution system", AIP Confeerence Proceedings, (AIP Publishing, 2018).
4. J.G. Roos, I.E. Lane, E.C. Botha and G.P. Hancke, "Using neural networks for non-intrusive monitoring of industrial electrical loads", Conference Proceedings of 10th Anniversary IMTC/94, (IEEE conference of Instrumentation and Measuremen, 1994*)*, pp.1115-1118.
5. Y.A. Lesnussa , C. Mustamu, F.K. Lembang and M. Talakua,, Int. J. Artif. Intell. **41-50, (**2018).
6. J. Zhang, X. Chen, W.W.Ng. C.S Lai and L.L. Lai L L, "New Appliance Detection for Nonintrusive Load Monitoring", (IEEE Trans. on Ind. Informatics, 2019), pp. 4819-4829.
7. Y. Liu, X. Wang and W. You, "Non-intrusive load monitoring by voltage–current trajectory enabled transfer learning", (IEEE Trans. Smart Grid 10, 2018), pp.5609-19.
8. J. Kim, T.T.H. Le and H. Kim, "Nonintrusive load monitoring based on advanced deep learning and novel signature", (Comput. intell. neurosci, 2017), pp.1-22.
9. A. Zoha, A. Gluhak, M.A. Imran and S. Rajasegarar, "Non-intrusive load monitoring approaches for disaggregated energy sensing: A survey" (Sensors 12, 2012), pp. 16838-16866.
10. S. Biansoongnern and B. Plungklang, "Non-intrusive appliances load monitoring (nilm) for energy conservation in household with low sampling rate", (Procedia Comput. Science. 86, 2016), pp. 172-175.
11. A.M. Sudoso and V. Piccialli, "Non-intrusive load monitoring with an attention-based deep neural network", preprint arXiv:1912.00759v1 [cs.LG] (2019).
12. Y. Li, B. Yin , P. Wang and R. Zhang, "Non-intrusive load monitoring based on convolutional neural network mixed residual unit", (Journal of Physics: Conf. Ser. 1176, 2019), pp.1-8.
13. D.S. Kumar, K.L. Low, A. Sharma and W.L. Woo, "Non-intrusive load monitoring using feed forward neural network", (IEEE Innov. Smart Grid Technol. - Asia (ISGT Asia), 2019), pp. 4065-4069.
14. M.Y. Yunus, M. Marhatang, A. Pangkung and M.R. Djalal, "Nilm based smart Meter design to monitor electrical energy use in the household sector using neural network", (Seminar Nasional Hasil Penelitian (SNP2M PNUP), 2018), pp. 83-88.
15. M.Y. Yunus, M. Marhatang, A. Pangkung and M.R. Djalal, "Design of a-based smart meters to monitor electricity usage in the household sector using hybrid particle swarm optimization-neural network", (International Journal of Artificial Intelligence Res. 3, 2019), pp. 70-81.
16. H.H. Chang, H.T. Yang and C.L. Lin, "Load identification in neural networks for a non-intrusive monitoring of industrial electrical loads", (International Conference on Computer Supported Cooperative Work in Design 5326, 2008), pp 664-674.

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